Chapter 14:

Genetically Modified Rice, International Trade, and First-Mover Advantage: The Case of India and China

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Introduction

During the last decade, a number of Asian countries have been actively developing programs of research on genetically modified (GM) crops (Runge and Ryan, 2004). Some of these countries have developed biosafety regulatory frameworks, but until now only a few have approved one or more GM crops. Empirical studies have shown that the introduction of Bt cotton in China and India have generated income gains for farmers overall (e.g., Bennett et al., 2004, Pray et al., 2002). But these two countries only approved the large scale production of GM cotton, in part because unlike other GM crops, the main products of cotton are not used for food, and thus are not subject to food safety approval and labeling regulations in major importing countries. In particular, neither Japan nor the European Union (EU) directly regulates textile products derived from GM cotton.

In fact, most Asian countries that have invested in research and regulations on GM food crops are confronted with three possible alternatives: 1) allowing the production of GM food crops with the risk of losing potential exports, 2) rejecting the commercialization of any GM food crop, 3) producing both GM and non-GM food crops separately at a marketing cost. At the same time, they have to take into account the potential opportunity cost of rejecting the technology when other competitors adopt it (Elbehri and MacDonald, 2004; Berwald et al., 2006). In the last few years, China has been conducting field trials of different varieties of GM rice but has delayed a decision on its formal approval. At the same time, India has been actively conducting public research on GM rice, but many officials appear reluctant to see its introduction. India's rice exports to sensitive markets are significant, but non-GM rice segregation could help preserve its exports while allowing the rest of the country to use GM rice

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to increase its agricultural productivity, and therefore help feed a large and fast-growing population.

This chapter provides an integrated ex-ante economic assessment of these strategies focusing on the case of GM rice resistant to biotic and abiotic stresses in India with or without GM rice introduction in China. More specifically, this chapter has three main objectives. First, we assess the impact of large importers´ regulations on the economic effects of GM rice adoption in India. Second, we evaluate the opportunity cost of GM/non-GM rice segregation under the external constraints previously defined. Third, we analyze the economic effects of GM rice adoption in India before or after China. In 2006, for the first time, India's total GM cotton area surpassed China's (James, 2006), despite the fact that India was a technology follower on Bt cotton. In this situation, it is relevant to ask whether India would gain or lose to jump ahead of China, and whether China would lose if India was a first-mover on GM rice.

Our approach is based on a multi-sector, multi-country, computable general equilibrium (CGE) model. We build our CGE model on previous studies measuring the international economic effects associated with the adoption of GM crops by improving the productivity assumptions and the representation of trade related regulations of GM food. In particular, we derive the expected effects of GM rice in India using spatially disaggregated primary and secondary data on constraints and technology potentials. At the same time, we use the assumptions of Huang et al. (2004) to model the adoption of GM rice in China, which are also based on regionally disaggregated estimates of productivity effects. These assumptions help us estimate the economic effects of adopting GM rice in these two countries under specific trade regulations and derive the opportunity cost of segregation of GM and non-GM rice in India, with or without China's adoption of GM rice.

The chapter is organized as follows. In the next section we briefly review the literature. Then, we describe the methodology employed to derive productivity shifts with the adoption of GM rice in India. Following this, we explain the specificities of our trade model and present our scenarios. The results of the simulations are then presented and discussed. Finally, we close the chapter with a few policy conclusions.

Previous Literature on GM Rice and International trade

Previous authors have used multi-country CGE models to simulate the introduction of GM crops. All models use versions of the GTAP database (Hertel, 1997) that includes vertical and horizontal linkages in the economy to examine the effects of GM technology adoption on multiple sectors and regions. The papers and approaches differ by their assumptions about the productivity effects of the technology, the rates of adoption, and according to the scenarios they choose to represent trade policies, consumer perceptions, and market assumptions. In this section, we focus on the CGE studies measuring the effect of GM rice adoption in developing countries, and we compare the results they obtain for India and China.[1]

Of the fourteen published CGE studies on GM crop introduction in developing countries (Smale et al., 2006), only five studies examine the effects of GM rice introduction in Asian countries. Two studies analyze the global effect of GM rice adoption, two studies focus on China, and one compares the effect of different GM rice varieties in eight Asian countries. Overall, these studies use similar approaches to modeling GM rice introduction, with productivity shocks in the regions of adoption. But they use different versions of the GTAP database, different sector and regional desegregations, and distinct assumptions concerning adoption rates, specific productivity effects and policies. We summarize the main differences in approach and assumptions and present the findings of these five studies in Table 1.

First, Anderson, Jackson and Nielsen (2004) provide an analysis of GM rice and golden rice (nutritionally enhanced rice) adoption in multiple countries, using factor-biased productivity shifts and running various trade scenarios. Their results show that golden rice would provide a much bigger boost to countries adopting it than other types of GM rice due to its assumed effect on labor productivity in all sectors. They also show that a ban of GM products in Europe and selected Asian countries would result in large net losses globally, even if countries like China and India would only be affected marginally and would still gain from GM rice adoption.

Anderson and Yao (2004) focus on China, and study the introduction of GM rice and cotton. They simulate the adoption of GM rice in North America, the Southern Cone of South America (Argentina, Uruguay, Chile), and South-East Asia with or without China. The results show that the global benefits with GM rice would double if China adopts it, with China's gains exceeding $1.1 billion per year. Two subsequent scenarios study the effects of GM food bans a) in Western Europe, and b) in Western Europe and North East Asia. The first case would reduce Chinese gains by $400 million while the second would divide by 3 the total welfare effects of

[1] A few other studies use partial equilibrium modeling approaches to model the introduction of GM crops. For the case of drought resistant rice, see Annou, Fuller and Wailes (2005), with plausible productivity shocks, and a better representation of the global rice market, but without trade restrictions.

Table 1: Summary of Applied General Equilibrium Analyses of GM Rice Introduction

Article GTAP version	Productivity assumptions	GM rice adoption	Scenarios	Welfare effects Global	 China	 India
Anderson, Jackson and Nielsen (2004) GTAP 5.4- 1997	Factor-biased productivity gains: For non-golden GM rice: 6% land, 8% labor, 5% chemical input. For golden rice: 2% unskilled labor efficiency gains in all sectors. Other crops: 5% Hicks-neutral shifts.	GM rice, coarse grains: 45% in USA & Canada, 30% in Argentina, 45% others (regular GM or golden rice). Oilseeds: 75% in USA, Canada and Argentina	a) China, South+ SE Asia adopt golden rice, Argentina, USA, Canada adopt GM oilseeds and coarse grains b) + ban in EU, Japan, Korea c) like a) with Bt rice d) same with coarse grains, oilseeds in Asia and ban of rice in EU, Japan, Korea	1997 USD a)$17438m b)$12060m c)$4379m d)-$5452m	1997 USD a)$7209m b)$7346m c)$871m d)$1001m	1997 USD a)$2528m b)$2528m c)$458m d)$696m
Anderson and Yao (2004) GTAP 4-1995 projected to 2005	5% Hicks-neutral productivity shift in all adopting countries	100% (implicit) in North America, South American Cone, South East Asia	GM rice Adoption a) Without China b) With China	1995 USD a)$804m b) $2019m	1995 USD a)$4m b)$1110m	1995 USD a)-18m b)-$23m
Huang et al. (2004) GTAP 5- 1997 projected to 2001-2010	Factor-biased productivity shifts: Dynamic changes in yields (from 6 to 7.03%), dynamic changes in pesticide costs (-52 to -65%), labor costs (-7.2 to -9.1%) and constant seed cost premium (50%).	Dynamic differentiation within China, national rate from 2% in 2002 to 40% in 2005 and 95% in 2010	a) Progressive adoption of Bt rice in China from 2002 to 2010 b) with ban in EU, Japan, Korea and SE Asia c) with labeling of GM food	Not provided	1997 USD a) $4155m b)-5% in total gains[a] c) -25% in total gains[a]	Not provided
Anderson and Jackson (2005) GTAP 5.4- 1997	5% Hicks neutral productivity shifts with GM rice or wheat in all adopting countries, 6% with oilseeds, 7.5% for coarse grains. 2% increase in all unskilled labor productivity with golden rice.	GM rice, wheat, coarse grains: 45% in USA and Canada, 30% in Argentina, 45% in others (GM and golden rice).Oilseeds: 75% in USA, Canada & Argentina	Selected scenarios: a) USA, Argentina, Canada, China and India adopt rice, wheat, coarse grains and oilseeds. b) same with EU moratorium c) all countries adopt no ban	1997 USD a)$4308m b)-$892m c)$7506m	1997 USD a)$841m b)$833m c)$899m	1997 USD a)$669m b)$654m c)$669m
Hareau et al. (2005) GTAP model not specified	Factor-biased shocks by trait and favorable and unfavorable land. Yield changed between 0 and 7.43%, for HT: seed cost (+15%) and labor cost (-15 to 30%)	Full adoption of Bt rice, drought resistant rice, limited adoption of HT rice in eight countries of Asia	Adoption of: a) Bt rice b) Drought resistant rice c) Herbicide tolerant (HT) rice	1997 USD a)$2278m b)$2522m c)$2169m	1997 USD a)$441m b)$230m c)$190m	1997 USD a)$522m b)$674m c)$487m

Source: Cited references
Note: a: In this case, total gains include GM rice and GM cotton adoption, and amount to $5,249m in 2010

GM crops. Overall the results show first that China would largely benefit from GM rice, and second, that as long as it keeps open access in the region it would largely benefit. Interestingly, the results for GM rice in India are negative, mostly because of a deterioration of its terms of trade with the price of rice declining.

Huang et al. (2004) provide an assessment of the effects of Bt rice and Bt cotton introduction in China, with significant improvements in productivity assessment and regulatory effects, but without explicitly accounting for adoption in any other country. They use dynamic factor-biased productivity shifts and adoption rates for GM rice. Their results show that China would gain about \$4.3 billion at a 95% adoption rate from the use of Bt rice by 2010. Total gains with Bt rice and Bt cotton would only be reduced by 5% with a ban of GM rice in EU and OECD Asian countries. However they estimate that the introduction of GM food labeling could reduce the gains with Bt cotton and Bt rice by 25%.

Anderson and Jackson (2005) study the effect of GM food crop adoption in Sub-Saharan Africa, including rice, but they also include the effect of GM rice adoption in India and China. They vary the elasticity of substitution between GM and non-GM to account for consumer aversion in OECD countries to all first-generation GM crops and increase consumer preference for golden rice in developing countries. They find that GM adopting countries largely benefit from GM rice and that trade restrictions are not significant compared to the potential gains for Sub-Saharan Africa. For India and China, they estimate that the gains from GM crop adoption would exceed \$650 and \$830 million, respectively, and they find that trade restrictions would not make much difference.

Lastly, Hareau et al. (2005) evaluate the effects of three different GM rice events (Bt rice resistant to stem borer, herbicide tolerant and drought tolerant) in eight countries of Asia. They use factor-biased productivity shifts, accounting for intra-national differences in land type, providing, therefore, a convincing approach to productivity modeling. Their results show that if the benefits of the three technologies are similar overall (over \$2billion/year), the distribution of benefits highly depend on the particular trait and type of land. However they do not account for the possible effect of trade restrictions.

To sum up, Table 1 shows there is a large variance in results across studies. For instance China would gain between \$200 million and \$4 billion by adopting non-golden GM rice. This variance can largely be explained by the differences in assumptions, particularly on productivity, but also by the modifications made to the model and differences in scenarios. At the same time, the effects of trade regulations on the benefits of GM rice seem to be relatively small for China. At the same time, India is used as a side country in four of the five studies, and there is an even larger variance in results for India across studies.

In this chapter we build on previous analysis by proposing an incremental improvement in two regards. First, as explained in the next section, we provide regionally based productivity effects in the country we focus on (following Hareau et al., 2005; or Huang et al., 2004). Second, as explained later in the chapter, we provide a more complex representation of international market regulations with trade filters, selective trade bans and segregation. At the same time, we focus on GM rice adoption in India, a large country that has not been the focus of previous work in this area and we analyze the effect of its adoption of GM rice before or after China.

Productivity Modeling

We model GM technology introduction with factor-biased productivity shifts in three dimensions: changes in yield, chemical use and labor productivity, using spatially disaggregated estimates of technology potential and adoption rates combined into national aggregate effects of technology in India. We also use expert data to formulate scenarios of adoptions accounting for plausible differences across types of land and overtime. This overall process is intended to help reduce uncertainties and replace what may appear as arbitrary productivity shifts by more consistent and plausible ones. In this section, we briefly explain the successive steps of the method used to derive our assumed productivity shifts in the four countries of study.

Collection of Expert and Secondary Data on Constraints and Technology Potential: We conducted a series of focus group meetings with scientific, agricultural and regulatory experts in India in July 2005 on the potential effects of biotechnology improvements providing resistance to biotic and abiotic stresses. In total, eight meetings were hold in five Indian cities (Delhi, Bombay, Bangalore, Hyderabad and Calcutta). In each of these meetings we discussed the status of research, agricultural constraints for rice and other crops, the potential of biotechnology to address these constraints, and other issues related to regulatory approval and consumer acceptance of transgenic crops. We also asked the participants to these meetings to fill out questionnaires in order to elicit subjective estimates of potential yield and input effects of future new technologies (as done for rice in Evenson et al., 1996). In parallel, we obtained existing national studies of rice productivity constraints and technology potential.[2]

Obtaining Range of Potential Technology Yield Effects in Affected Areas:[3] We focus on four types of traits: insect resistance (more specifically Bt resistance to the stem borer), disease resistance (bacterial blight), drought resistance and salt tolerance. Each GM rice variety is modeled based on its effect on yields, use of chemical inputs (mainly pesticides), and its effect on labor. We would have liked to include the cost of seeds as a third factor, but we later realized that we did not have relevant data to incorporate it into our trade model. We justify the exclusion of seed premiums by choosing exogenous adoption rates that reflect partial adoption due to seed price differences. As a consequence, our results will be inclusive of the benefits of developers and not only producers (unlike Huang et al., 2004).

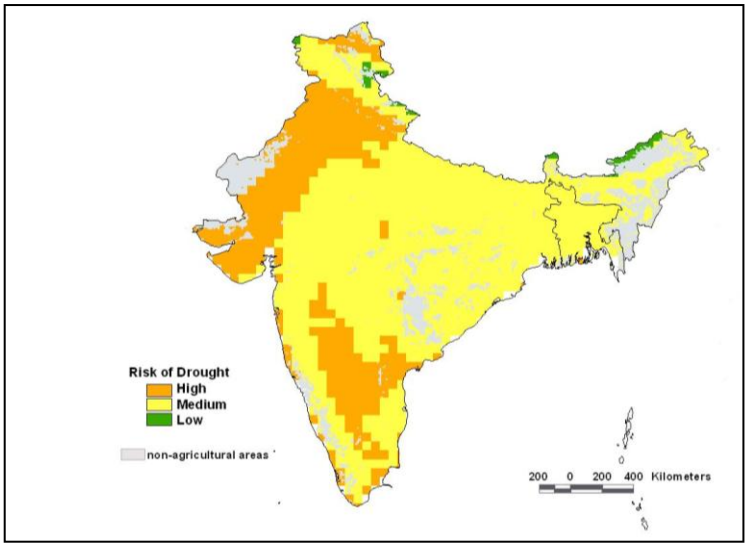
Combining expert estimates on constraints and productivity potential and secondary data on yield constraints, we derived expected yield effects in rain fed versus irrigated land and in each water basin region of India.[4] Triangular distributions of yield constraints (or yield gap) and of the potential effects of using transgenic crops from the questionnaires and meetings are aggregated by taking the "minmin" and "maxmax" values and by averaging the most likely values (excluding clear outliers). We compute average ranges of potential effects by averaging over the most likely values of yield constraints (or yield gap) from different data sources, with the minimum and maximum values retained. The ratio of expected yield effects on yield constraints derived from experts' data is used as a proxy for the expected efficacy of the technology. This efficacy rate is multiplied by the yield gap associated with the constraint to obtain the range of most likely yield effects of the technology.

Affected Land and Production Type by Water Basin Projection: The resulting yield effect is multiplied by the production share for each sub-region represented by a particular type of land (irrigated or rain fed) and water basin in India in order to obtain a weighted average of the total yield effects for India. To do so, we used 2015 projections of irrigated and rain fed areas by water basins in India from a baseline simulation of the IMPACT-Water model developed at the International Food Policy Research Institute (IFPRI). IMPACT-Water is a multi-market partial

[2] The complete list of sources can be obtained from the authors.
[3] In this section, we focus on the derivations of the yield effect. The derivations of the input effects were mostly based on a combination of primary and secondary data per crop/trait combination, but did not involve triangular distributions.
[4] In this subsection we describe more specifically the derivation of yield effects, for which we use triangular distributions, but our derivations of the input effects also follow the same general procedure.

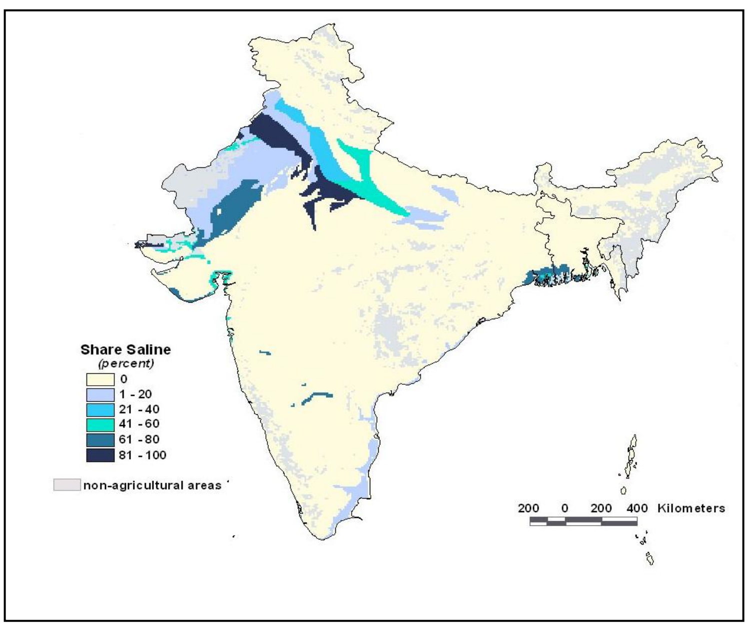
equilibrium model of agricultural production and trade at the water basin level that projects the evolution of land and agriculture. The combination of yield effect by sub-region and share of each sub-region generates national average yield effects of each rice technology assuming a 100% adoption rate.

Figure 1: Spatial Drought Risk Indicator in India



Source: IFPRI (2005)

Figure 2: Salinity Risk Indicator in India



Source: IFPRI (2005)

For the case of rice resistant to abiotic stresses, i.e. drought and salt tolerant rice, we also estimate the share of affected areas in each sub-region in order to account for the fact that not all land is affected by drought or soil salinity constraints. To do so, we used categorical indicators of drought and salinity constraints (see Figures 1 and 2) by areas of production, type of land, and water basin based on a satellite imagery and agricultural study developed by the spatial team of IFPRI.[5]The measure of drought is based on the annual variation (around a three decade average) of the length-of-growing-period computed for each of the 30 years from 1961-1990 (Fischer et al., 2002). The soil salinity index is based on a Fertility Capability Classification approach (Smith et al., 1998; Sanchez et al., 1982) applied to the mapping units of the FAO Soil Map of the World (FAO, 1995). The results allowed dividing the land into 10 types of categories of risk based on the share of saline land in each spatial unit.

By filtering these indicators with production area in each spatial unit, we obtained the share of affected areas in each sub-region. We then built categorical yield responses to the risk of drought or salinity. For instance, in the case of drought, the IFPRI spatial team was able to classify delimited areas of land in four categories: no risk, low risk, medium risk and high risk. We attributed probability of risk for each category (using a linear approximation) to obtain expected damage due to drought in a particular sub-region. The output is a weighted average of damage in each sub-region representing the national effect of abiotic stress resistant crops with a 100% adoption rate among producers affected.

Adoption: Expert Data and Secondary Data on High Yield Varieties Adoption: In this study, we assume that producers in rain fed areas will not have the same adoption rate as producers in irrigated areas. Generally speaking, producers in irrigated areas tend to have a better access to new technologies, but at the same time, rain fed producers may benefit more from certain technologies.

In addition, regional differences matter, and in a country like India, certain States tend to be the first to provide and adopt new technologies and have a higher proportion of technology adopters. To account for this fact, we corrected the production share of each Indian region by a proportional factor linked to historical data of the adoption of high yielding varieties of rice obtained from IndiaStat. Instead of assuming that a GM crop will be adopted in all regions the

[5] The detailed mapping methodology, using an entropy approach to spatial disaggregation is explained in detail in You and Wood (2006). Abiotic stress indicators were developed by Liang You, Stan Wood, and Cynthia Rossi, following a methodology explained in detail in IFPRI (2005) for India.

same way, we let certain region be relatively larger adopters of the crop. The adoption rate in each sub-region is then multiplied by each yield and area factors to obtain a total expected yield effect of the technology in 2010, 2015 and 2020.

Obtaining Land Type Aggregate Effect and National Effects: The aggregate national effect of the technology is computed with the following formula:

(1) $$\sum_{l}\left(\sum_{w} a_{lt}\beta_{w}\sigma_{lw}y_{lw}.\lambda_{lw}\right).$$

The subscript l stands for type of land: irrigated or rain fed, the subscript w for the water basin, and t for time; a is the exogenous adoption rate per type of land (for abiotic stress it represents the adoption among producer affected) and period, β the proportional spatial correction of adoption rate based on observed rates of adoption of high yielding varieties in each water basin, σ is the share of production of the crop in the sub-region, y is the yield effect in each sub-region, and λ is the share of production under rain fed or irrigated affected by a specific abiotic stress. Fourteen water basins are used to represent India.

Table 2: Absolute Productivity Effects and Initial Adoption assumed for India

India	**% Yield effects**			**% Input effects**		**% Adoption initial**		
Technology	Min	ML	Max	Chemicals	Labor	IR	RF	Total
DR Rice	0.30	2.58	6.69	0	0	24.55	18.4	22.43
ST Rice	0.37	1.97	3.76	0	0	9.95	4.06	7.91
Bt Rice	0.30	1.03	2.13	-9.5	-2.31	60	10	27.6
VR Rice	0.11	0.43	0.87	-0.97	-0.4	30	5	13.8

Source: Authors. Note: ML: most likely, DR: drought resistant, ST: salt tolerant, VR: virus/disease resistant, IR: irrigated, RF: rain fed

Assumptions for the Major Technologies in India and China: The assumptions derived from this process for India are presented in absolute terms in Table 2. This table presents the assumed effects of each GM rice technology projected in 2015, which are the ones we use in our simulation model.[6] The parameters presented in these tables include minimum, most likely and maximum value of the total yield effect, the total chemical effects, and the total labor effects at the national level under the initial adoption rate presented in the last three columns. For instance, the introduction of drought resistant rice in India (first row of Table 2) at an initial

[6] We also derived the effects and adoption for each crops in 2010 and 2020, but we did not use them in the simulations presented in this chapter. We plan to use them later by adopting a dynamic modeling approach.

adoption rate of 22.43%, corresponding to 24.55% of irrigated land and 18.4% of rain fed land in 2015 would most likely result in a 2.58% increase in total rice production in India.

To translate these data into usable inputs in the multi-market, CGE model, we computed the hypothetical yield and input effects at 100% adoption level. To do so, we divided the estimated aggregate national effects by the estimated national adoption rates (computed as a weighted average of the adoption rate for irrigated and rain fed land). We then added the estimated aggregate national effects for each trait and divided them by the total adoption rate for each crop. These parameters are presented for reference in the first row of Table 3, but it is important to note that they are not necessarily meaningful, even if they are directly derived from estimated adoption and yield and input effects following the methodology described in this section. [7] In the case of China, in absence of primary data, we use the assumptions made by Huang et al. (2005) for 2010, while moderating the initial adoption rate. The parameters are shown in relative terms in the second row of Table 3.

Table 3: Relative Productivity Effects and Initial Adoption Rates assumed for China and India

Country	**% Yield effects**	**% Input effects**		**% Adoption**
		Chemicals	Labor	
India	8.38	-14.59	-3.78	71.74
China*	7.03	-65	-9.1	80

**Source*: Huang et al. (2004)

Trade Modeling and Scenarios

A modified version of the MIRAGE model (Bchir et al., 2002) is used to simulate a range of scenarios on the productivity effect, trade restrictions and segregation options.[8] This model is based on the GTAP 6.1 database, which represents the world as of 2001. For this application, we divide the economy into 21 regions, including GM producing countries, sensitive importing countries and other important countries, and 19 sectors, including the relevant production sectors, as well as the chemical sector. The MIRAGE model includes an updated representation of trade policies and unilateral, bilateral and multilateral trade preferential agreements (using MAcMap-HS6; 2001 data).

We first modify the MIRAGE model by dividing the rice sector into GM and non-GM

[7] For example, it does not make sense to consider the effects of 100% national adoption of a drought resistant variety when the productivity effects of such variety will only be effective in 10% of the land.
[8] The MIRAGE model was developed at the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) in Paris. Full description of the model is available at the CEPII website (www.cepii.fr).

substitutes for all GM adopting countries. Second, with this structure, the model is changed to allow for the use of specific productivity shocks only on GM products in each GM sector for each adopting countries. The model is also modified to allow for the selective ban of GM and/or non-GM imports going towards the final consumption in selected countries only from GM producing nations. This is done to reflect the current effects of labeling policies, which have allowed certain products to get into sensitive countries (animal feed in the EU, soy oil in Japan), but not others (Gruere, 2006). Furthermore, the model allows for blocking of imports from GM producing countries going towards both final and intermediate consumption of rice in certain scenarios. Lastly, the model is changed to allow for the introduction of a segregation cost for non-GM going from GM adopting countries to sensitive importing ones.

To calibrate the model, we use the assumed parameters provided in the previous section regarding the productivity shocks and the proposed adoption rates. However because of the relative aggregated level of the chemical sector GTAP database, we make adjustments on the chemical input shock. In particular we reduce the productivity shock proportionally to account for the share of pesticide costs into the aggregated GTAP chemical sector for GM rice in the two adopting countries. More specifically, we use a two-step approach, first deriving the share of fertilizer in chemical use from FAOSTAT 2001, and secondly using general data on the share of insecticides in total pesticide use at the continental level (Yudelman et al., 1998).

After this data adjustment, under each set of scenarios, the model is calibrated to incorporate the assumed productivity shock in the GM adopting nations. This process results in adaptation of the models to the productivity shock and adoption rates allowing the balance of factors and sectors in the economy as represented in the model. Then under each scenario, we run the model only once to simulate a comparative static shock and the relevant trade restrictions. We use a perfect competition representation of the economy for simplification. Further refinements of our simulations could include modeling dynamics and imperfect competition.

We define three distinct sets of scenarios. The first (Set C) only includes China as a GM rice adopter. In our consultation meetings, we found that Indian scientific and regulatory experts believe that India will only adopt GM rice if China adopts it first. The second (Set I) makes India the leading adopter of GM rice. The third (Set CI) represents the case of the adoption of GM rice in the two countries. Each set of scenarios comprise eight individual scenarios, as shown in Table 4.

Scenario 0 is run as a benchmark without GM production. Scenario 1 simulates a productivity shock associated with the adoption of GM rice and no trade restriction, i.e., assuming all countries import and consume GM and non-GM rice with no differentiation. Scenario 2 includes the same productivity shock with trade restrictions and no segregation. More specifically, we distinguish two sub-scenarios 2a and 2b. Sub-scenario 2a represents the short run effect of the adoption of unapproved GM rice varieties, namely the ban of GM and non-GM crops in sensitive countries. Sub-scenario 2b represents current trade restrictions on GM imports in sensitive countries. Current marketing regulations, private standards and consumer reactions act as a trade filter. Products to be used for final consumption are not purchased or approved, but products for intermediate consumption (such as animal feed) are allowed because the final products are still used and are not necessarily subject to labeling requirements (e.g. meat in the EU, for more on labeling, see Gruere and Rao, 2007).

Table 4: Features of Each Scenario for GM Adopting Countries under each Set

Scenario number and title	Productivity shock on GM crops	Ban towards the intermediate consumption in sensitive countries[a] of		Ban towards the final consumption in sensitive countries[a] of		Segregation of non-GM product exported towards sensitive countries[a]
		Non-GM	GM	Non-GM	GM	
0. Base	No	No	No	No	No	No
1. Productivity shock	Yes	No	No	No	No	No
2a. Import ban, no segregation	Yes	Yes	Yes	Yes	Yes	No
2b. Import filter, no segregation	Yes	No	No	***Yes***	Yes	No
3a-i. Import ban, costless segregation	Yes	No	Yes	No	Yes	Yes
3a-ii. Import ban, 5% cost segregation	Yes	No	Yes	No	Yes	Yes
3b-i. Import filter, costless segregation	Yes	No	No	No	Yes	Yes
3b-ii. Import filter, 5% cost segregation	Yes	No	No	No	Yes	Yes

Note: a :The sensitive countries are the European Union, Rest of Europe, Japan, South Korea and Australia-New Zealand

Lastly, scenario 3 allows for the segregation of non-GM exports from GM adopting countries to sensitive importing countries. Three sub-scenarios are proposed to study the implication of different segregation costs and types of trade restrictions; 3a-i is ran with costless segregation (as a benchmark) but ban of GM in final and intermediate consumption of sensitive countries (based on scenario a), 3a-ii is the same with a 5% basic segregation cost, 3b-i is based on scenario 2b with costless segregation of non-GM, and 3b-ii adds a 5% segregation cost.

Results

We present the results in terms of welfare effects, defined as the equivalent variation (or real income) between each scenario and the base (0) for each set. Both absolute values in millions of dollars and percentage of total real income per year are shown for each region in each scenario. We also provide additional data on production, imports, exports and prices in the Appendix (see Tables A1, A2, A3, and A4) to explain the results.[9]

Set C: Table 5 shows the results for the Set C. In this case, China is the only country to adopt GM rice. The United States approved the use of herbicide tolerant rice in 2006, but it is not cultivated because of fears of export losses. Iran has reportedly approved the cultivation of Bt rice, and could be the only country producing GM rice at a small scale (James, 2006). We decided to neglect limited potential GM rice production in these two countries, in order to isolate the shock with the adoption of GM rice in China (and/or India in other sets). It is commonly believed that GM rice will be available in world markets only if it is first released in China.

The productivity shock generates global welfare gains exceeding $5.6 billion, most of which are attributed to China ($4.6 billion). The introduction of an import ban in sensitive countries (scenario 2a) reduces global gains by about $1.3 billion, most of which is due to a reduction in welfare gains in these particular countries. In contrast, an import filter in sensitive countries reduces global gains by only $300 million. This means that, with the adoption of GM rice, rice exports from China to sensitive countries will be more largely directed towards intermediate than towards final consumption. The introduction of segregation with an import ban (scenarios 3a-i and 3a-ii) results in significant increases in global gains (from $460 to 600million), even with

[9] The price indicator can be misleading since it is just a weighted average of numerous price evolutions which does not reflect well the eventual unequal distribution of prices. MIRAGE export prices are determined by products, country of origin, and country of destination and there is no single world price for a commodity.

Table 5: Change in Welfare Effects under Each Scenario with GM Rice Adoption in China ($ million/year and % total)

GM rice adopted in bold regions Set C	**1. Productivity shock**		**2a. Import ban, no segregation**		**2b. Import filter, no segregation**		**3a-i. Import ban, costless segregation**		**3a-ii. Import ban, 5% segregation cost**		**3b-i. Import filter, costless segregation**		**3b-ii Import filter, 5% segregation cost**	
Region	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%
Australia and New Zealand	-3.931	-0.001	-1.964	-0.001	-3.781	-0.001	-2.958	-0.001	-2.840	-0.001	-3.881	-0.001	-3.860	-0.001
China	4631.580	0.596	4607.905	0.593	4623.713	0.595	4617.701	0.594	4615.728	0.594	4626.803	0.596	4625.692	0.595
Japan	441.544	0.014	-293.716	-0.010	155.614	0.005	36.312	0.001	-31.578	-0.001	281.734	0.009	232.040	0.008
South Korea	171.091	0.059	-154.111	-0.053	146.833	0.051	8.038	0.003	-23.123	-0.008	158.080	0.055	142.878	0.049
Rest of Asia	13.547	0.002	13.498	0.002	14.202	0.003	13.362	0.002	14.062	0.003	13.878	0.002	14.450	0.003
Indonesia	2.728	0.003	3.146	0.003	2.810	0.003	2.945	0.003	3.012	0.003	2.771	0.003	2.820	0.003
Philippines	3.910	0.006	3.004	0.005	3.698	0.006	3.424	0.005	3.313	0.005	3.792	0.006	3.719	0.006
Bangladesh	0.457	0.001	0.304	0.001	0.437	0.001	0.376	0.001	0.420	0.001	0.446	0.001	0.492	0.001
India	-0.195	0.000	0.543	0.000	-0.032	0.000	0.212	0.000	-1.431	0.000	-0.105	0.000	-1.620	0.000
Canada	6.015	0.001	6.311	0.001	6.159	0.001	6.169	0.001	6.227	0.001	6.091	0.001	6.141	0.001
United States	73.624	0.001	74.402	0.001	74.761	0.001	73.979	0.001	73.609	0.001	74.251	0.001	73.925	0.001
Mexico	3.161	0.001	2.498	0.001	3.006	0.001	2.807	0.001	2.721	0.001	3.074	0.001	3.016	0.001
Rest of Latin America	28.967	0.006	31.867	0.006	29.828	0.006	30.523	0.006	30.964	0.006	29.441	0.006	29.742	0.006
Argentina	-0.051	0.000	0.172	0.000	-0.030	0.000	0.070	0.000	0.092	0.000	-0.041	0.000	-0.029	0.000
Brazil	-0.140	0.000	0.033	0.000	-0.083	0.000	-0.040	0.000	-0.010	0.000	-0.109	0.000	-0.083	0.000
European Union	206.655	0.003	-0.406	0.000	129.536	0.002	89.921	0.001	53.499	0.001	162.154	0.003	134.016	0.002
Rest of Europe	26.825	0.004	9.708	0.001	18.455	0.003	17.123	0.003	15.109	0.002	22.058	0.003	20.404	0.003
North Africa and Middle East	31.349	0.004	29.892	0.004	31.380	0.004	30.521	0.004	30.573	0.004	31.354	0.004	31.470	0.004
Rest of Sub-Saharan Africa	46.272	0.029	45.449	0.028	46.267	0.029	45.771	0.028	45.724	0.028	46.258	0.029	46.248	0.029
South Africa	1.491	0.002	1.334	0.002	1.489	0.002	1.411	0.002	1.388	0.002	1.490	0.002	1.477	0.002
Tanzania and Uganda	0.553	0.004	0.496	0.004	0.548	0.004	0.521	0.004	0.520	0.004	0.550	0.004	0.551	0.004
World	**5685.449**	**0.023**	**4380.366**	**0.018**	**5284.807**	**0.022**	**4978.186**	**0.020**	**4837.978**	**0.020**	**5460.087**	**0.022**	**5363.487**	**0.022**

Source: Authors' results from simulations

a 5% cost of segregation. Similar relative compensating welfare effects are observed with costless or costly segregation scenarios based on import filters (3b-i and 3b-ii). Costly segregation scenarios (at 5%) result in a small decline in global welfare compared to costless segregation, mainly because of a reduction in welfare gains in sensitive countries largely due to, the increase in import prices they face.

Therefore, at the global level, one can conclude that the introduction of GM rice would result in gains of about $5billion/year, most of which would go to China. Trade restrictions in sensitive countries in the short run (ban) would result in reduced global gains, mostly because of smaller gains in these importing countries. Trade restriction in sensitive countries in the long run (filter) would result in much smaller reductions in welfare gains. Segregation of non-GM rice can help compensate for trade losses. Costly segregation leads to market segmentation and a price increase for rice imports in sensitive countries.

China's gains are almost identical across scenarios, ranging from $4608 to $4631 million annually. The decomposition of welfare (Table A1) shows that China only receives small allocative efficiency gains and terms of trade gains. Most of its welfare gains come from other sources, including technical gains.[10] With the introduction of GM rice (scenario 1), China increases its production by 20%, increases its exports by 27% and reduces its imports by 47%, but these relative changes vary across scenarios. In particular, under trade restriction and no segregation (scenarios 2a and 2b), China does neither produces nor exports as much, which may explain its reduction in total gains. In fact with an import ban on rice in sensitive countries, China exports 12% less rice than in the base. In contrast, when adding segregation to an import ban, China exports much more rice than in the base (40 to 60%), mostly non-GM rice going towards sensitive countries, as it is taking advantage of a good price for non-GM. As a consequence, whether costly or costless, segregation helps in offsetting the relative reduction in welfare gains with a trade ban. In the long run, assuming sensitive countries' regulations act as trade filters allowing intermediate consumption, segregation also provides small relative gains to China even at 5% additional costs; in particular, the production of rice reaches +20% with lower export increases.

In Set C, India is not producing GM rice. As a rice exporter to sensitive countries, India would lose about $0.2 million/yr from the free adoption of GM rice in China. Results show that

[10] In the three sets, the welfare decomposition does not change significantly across scenarios.

India produces only a little less and exports 5.7% less rice in scenario 1 (Table A3). With a trade ban or trade filter on GM rice in sensitive countries, India's gains or losses are insignificant. India incurs slightly larger losses with costly segregation in sensitive countries, as its total rice exports decline by 8 to 9% compared to the base. India obtains small gains under the total ban scenario (2a), probably gaining market shares. Overall, none of the effects of GM rice introduction in China is significant in terms of India's total real income. In fact, other countries are more affected than India by China's adoption of GM rice. In relative terms, the largest average gains occur in Sub-Saharan Africa, a region that imports rice. South Korea gains more in relative terms for the three scenarios with trade filters than with trade bans, as it imports some rice for intermediate consumption from China. Only two regions experience small losses across all scenarios, Australia-New Zealand, a small competitor, and Brazil, but as with India, these losses are insignificant in relative terms.

Set I: In the second set, India is the only producer of GM rice. This more hypothetical scenario helps to isolate the effect of GM rice adoption under trade restrictions in India. Moreover, it provides an insight into the effect of India preceding China in adopting GM rice. The welfare results of this set of scenarios are provided in Table 6. Global welfare gains exceed $3.5 billion annually. The almost entire gains occur in India ($3.2 b). Global gains are highest in scenario 1, with only productivity shocks. Trade restrictions in sensitive countries reduce the overall gains by about 2 to 6%. The use of costless segregation partially compensates this relative reduction in gains for both trade ban and trade filter. But with 5% costs of segregation, global welfare gains decline to a lower level than the ones with trade restrictions and no segregation. Therefore, it is clear that, if India is the only adopter of GM rice, the cost of segregation, rather than the type of restriction, is an important factor in the outcome.

India gains over $3.25 billion in real income with GM rice adoption. Although these gains are smaller than the one in China in Set C, they are larger in relative terms. Most of these gains come from improvements in technical and allocative efficiency (Table A1). As an important exporter, the adoption of GM rice in India results in a larger drop in average world price than in the case of China (-0.8% instead of -0.6% in Set C), which may partially explain the small drop in India's terms of trade (-0.01% of total real income). Because India is exporting a significant share of rice towards sensitive countries, trade restrictions affect its outcome relatively more than China in Set C, but these reductions still remain quite small in absolute terms (about $21 million

Table 6: Change in Welfare Effects ($ million/yr and % total) under each Scenario with GM Rice Adoption in India

GM rice adopted in bold regions Set I	1. Productivity Shock		2a. Import ban, no segregation		2b. Import filter, no segregation		3a-i. Import ban, costless segregation		3a-ii. Import ban, 5% segregation cost		3b-i. Import filter, costless segregation		3b-ii Import filter, 5% segregation cost	
Region	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%
Australia and New Zealand	-1.184	0.000	-1.720	-0.001	-1.685	-0.001	-1.438	0.000	-1.300	0.000	-1.417	0.000	-1.287	0.000
China	5.042	0.001	4.740	0.001	4.902	0.001	4.892	0.001	2.895	0.000	4.973	0.001	3.055	0.000
Japan	33.837	0.001	6.421	0.000	23.799	0.001	20.369	0.001	-57.507	-0.002	28.845	0.001	-48.126	-0.002
South Korea	8.815	0.003	0.233	0.000	8.095	0.003	4.562	0.002	-29.519	-0.010	8.452	0.003	-25.027	-0.009
Rest of Asia	-14.421	-0.003	-8.695	-0.002	-12.887	-0.002	-11.992	-0.002	-11.360	-0.002	-13.742	-0.002	-13.395	-0.002
Indonesia	5.883	0.006	6.186	0.006	5.945	0.006	6.008	0.006	6.081	0.006	5.909	0.006	5.968	0.006
Philippines	1.849	0.003	1.597	0.003	1.790	0.003	1.737	0.003	1.615	0.003	1.822	0.003	1.714	0.003
Bangladesh	2.904	0.008	3.372	0.009	3.069	0.008	3.101	0.008	3.137	0.008	2.976	0.008	2.996	0.008
India	3262.894	0.875	3243.777	0.870	3256.189	0.873	3254.683	0.873	3253.050	0.872	3259.908	0.874	3258.959	0.874
Canada	2.682	0.001	2.915	0.001	2.775	0.001	2.776	0.001	2.839	0.001	2.722	0.001	2.776	0.001
United States	23.573	0.000	20.031	0.000	22.905	0.000	22.000	0.000	21.769	0.000	23.267	0.000	23.183	0.000
Mexico	1.530	0.000	1.317	0.000	1.471	0.000	1.433	0.000	1.333	0.000	1.502	0.000	1.412	0.000
Rest of Latin America	-0.471	0.000	1.143	0.000	-0.098	0.000	0.205	0.000	0.667	0.000	-0.308	0.000	0.059	0.000
Argentina	-1.519	-0.001	-1.461	-0.001	-1.557	-0.001	-1.490	-0.001	-1.462	-0.001	-1.536	-0.001	-1.514	-0.001
Brazil	-0.728	0.000	-0.523	0.000	-0.686	0.000	-0.636	0.000	-0.609	0.000	-0.709	0.000	-0.690	0.000
European Union	114.210	0.002	-42.832	-0.001	50.905	0.001	43.686	0.001	5.022	0.000	85.108	0.001	52.245	0.001
Rest of Europe	7.904	0.001	3.103	0.000	5.773	0.001	5.639	0.001	3.375	0.001	6.896	0.001	4.745	0.001
North Africa and Middle East	68.884	0.009	70.764	0.009	69.755	0.009	69.596	0.009	69.646	0.009	69.247	0.009	69.245	0.009
Rest of Sub-Saharan Africa	28.929	0.018	29.263	0.018	29.244	0.018	29.027	0.018	28.957	0.018	29.059	0.018	28.989	0.018
South Africa	11.214	0.013	11.209	0.013	11.221	0.013	11.201	0.013	11.190	0.013	11.214	0.013	11.204	0.013
Tanzania and Uganda	0.951	0.007	0.991	0.007	0.970	0.007	0.966	0.007	0.965	0.007	0.959	0.007	0.956	0.007
World	**3562.778**	**0.015**	**3351.829**	**0.014**	**3481.894**	**0.014**	**3466.325**	**0.014**	**3310.781**	**0.014**	**3525.148**	**0.014**	**3377.465**	**0.014**

Source: Authors' results from simulations

or 0.6% of total gains with trade ban compared to scenario 1). With GM rice, India increases its production by about 20% and reduces its imports by over 50% (Table A4). Changes in rice exports vary across scenarios, from + 17.7% in the most restrictive scenarios 2a and 2b to +26% in scenario 1 and +39% in scenario 3a-i.

In the short run, with sensitive countries banning all rice imports from India, India still gains over $3.243 billion annually. Segregation of non-GM rice can increase these gains by a small amount ($10 million), even with 5% costs. With segregation, Indian rice exports would increase by over 30% compared with the base scenario with no GM rice, most of which will be non-GM rice going towards sensitive countries because of the better price they can fetch there.

In the long run, with trade filters in sensitive countries, the same pattern occurs on a smaller scale. A trade filter reduces the gains to India by $7 million/year, of which costless segregation compensates $3 million/year, thanks to an increase of rice export by about 12% relative to the base. India can still benefit from segregation with 5% costs, increasing its exports by 5% and obtaining an additional $2 million/year compared to no segregation.

In Set I, China does not adopt GM rice, despite being more advanced in the technology. China has been testing GM rice in the field for the last few years, yet it still has not decided to approve or reject its commercialization. Results for this set of scenarios show that, if India becomes a technology leader through introducing GM rice, China would not lose in welfare overall. In fact it would gain a very small amount ($3-5 million annually). The main consequence of India's adoption of GM rice is a reduction of Chinese rice exports by 4 to 12%. Rice production in China decreases by an insignificant amount, while imports increase by about 1%. The welfare results do not change significantly across scenarios, even if the segregation for Indian rice with 5% costs would result in slightly smaller gains.

Among other countries, the largest relative gains occur in the Rest of Sub-Saharan Africa and South Africa. Because of the increased competitiveness of India and the decline in average prices, exporters like the Rest of Asia (the leading rice exporting region), Argentina, Australia and Brazil consistently incur losses across scenarios, even if all losses are very small in relative terms. Sensitive Asian importers lose with costly segregation schemes and account for a large share of the differences in global gains across scenarios.

Set CI: The results for the Set CI, with GM rice introduction in China and India, are presented in Table 7. Global gains amount to a little less that the addition of the two amounts obtained in the previous sets, reaching $9.2 billion under scenario 1. These gains vary between $7.7 and 9 billion across scenarios with trade restrictions. As in the previous cases, most of the gain occurs in countries adopting GM rice, but the differences across scenarios are mostly due to the variation of welfare in sensitive countries. Trade ban and trade filter for rice produced in China and India without segregation result in a reduction of global gains by 16 and 7%, respectively. The difference between the two demonstrates once again the relative importance of rice going from China and India towards the intermediate consumption of sensitive countries. In the short run, segregation would help recuperate 38 to 48% of the welfare gain reduction due to a trade ban. In the long run, segregation of non-GM rice for final consumption increases global gains by an insignificant amount in relative terms, but still compensating for 27 to 46% of the reduction in global gains with trade filters.

China gains $4.6 billion annually (corresponding to 0.6% of total real income) from introducing GM rice, an amount almost identical to the one obtained in Set C. The decomposition of welfare is exactly the same as the one in Set C. Therefore, the adoption of GM rice in India does not result in any significant loss for China, even if the average price index of rice decreases by over 1.3% instead of 0.5% compared to the base. Overall, China increases its rice production by 18 to 20%, and decreases its imports by over 46% (Table A5). China’s exports changes vary across scenarios, contributing to the small changes in welfare. In the short run, a ban of rice in sensitive countries results in an increase of Chinese rice exports by 8% compared to 21% in scenario 1, but the reduction of total welfare gains is still limited to about $34 million/year. Segregation of non-GM rice translates into relatively less rice production and a large relative increase in rice exports (up to 51% compared to the base), mostly of non-GM rice directed towards sensitive countries. Costly segregation slightly reduces the non-GM exports but is still beneficial compared to no segregation. In the long run, applying a trade filter in sensitive countries, results in a similar increase of exports of 7%. Segregation of non-GM rice partially compensates for the small reduction in welfare gains, and is translated by export increases up to 30% compared to the base. Most of these exports are non-GM rice going towards sensitive countries.

In average, India gains $3.253 billion annually (or 0.872% of total real income) with the adoption of GM rice, a total only remotely inferior to the one with India adopting alone ($3 million lower). The decomposition of welfare remains the same, with a small loss in terms of trade, but relative technical and allocative efficiency gains (Table A1). India increases its production of rice by 16 to 20%, and its imports decrease by over 51%. Like China, changes in exports vary across scenarios. In the short run, a trade ban in sensitive countries results in a loss of $18 million/year. Segregation of non-GM rice towards sensitive countries provides a significant compensation (around $11million/year), based on a relative large increase in exports of non-GM rice towards sensitive countries. In the long run, import filters in sensitive countries only result in a reduction of gains by $6 million per year compared to scenario 1. With segregation, India regains about $3-4 million, thanks to increased exports of non-GM rice towards sensitive countries.

Among other countries, African countries are the only one with consistent and relatively significant gains with the adoption of GM rice in India and China because of the price decrease. Australia-New Zealand, Argentina, and Brazil incur small losses, as rice exporters. At the same time, the largest rice exporters, located in the Rest of Asia region, do not incur net welfare losses, but obtain insignificant gains despite reducing their production of rice by about 2% and their exports of rice by more than 13%. Brazil, Bangladesh, Indonesia and the Philippines increase their total rice imports in all scenarios, therefore contributing to the absorption of the rice production increase in India and China. The three Asian countries in this group obtain small gains overall, while Brazil incurs losses.

Lastly, the results for sensitive importers vary largely across scenarios. Japan, South Korea and the EU import more rice in the scenarios with a GM ban and segregation, but not in other scenarios. Apart from Australia and New Zealand, only Japan and South Korea lose with GM rice under scenario 3a-ii, with a 5% segregation cost and ban of GM

Table 7: Change in Welfare Effects ($ million/yr and % total) under each Scenario with GM rice Adoption in China and India

GM rice adopted in bold regions Set CI	**1. Productivity Shock**		**2a. Import ban, no segregation**		**2b. Import filter, no segregation**		**3a-i. Import ban, costless segregation**		**3a-ii. Import ban, 5% segregation cost**		**3b-i. Import filter, costless segregation**		**3b-ii Import filter, 5% segregation cost**	
Region	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%
Australia and New Zealand	-4.959	-0.002	-3.528	-0.001	-5.313	-0.002	-4.276	-0.001	-4.151	-0.001	-5.146	-0.002	-5.119	-0.002
China	4633.467	0.596	4609.906	0.593	4625.684	0.595	4620.240	0.595	4618.276	0.594	4628.876	0.596	4627.751	0.596
Japan	472.340	0.015	-288.651	-0.009	177.276	0.006	56.301	0.002	-11.778	0.000	308.451	0.010	259.205	0.009
South Korea	178.413	0.062	-155.699	-0.054	153.534	0.053	12.564	0.004	-18.638	-0.006	165.156	0.057	150.179	0.052
Rest of Asia	1.535	0.000	7.360	0.001	3.657	0.001	3.275	0.001	3.962	0.001	2.404	0.000	2.774	0.001
Indonesia	8.500	0.009	9.222	0.009	8.640	0.009	8.828	0.009	8.902	0.009	8.566	0.009	8.611	0.009
Philippines	5.656	0.009	4.481	0.007	5.384	0.009	5.081	0.008	4.968	0.008	5.517	0.009	5.451	0.009
Bangladesh	3.382	0.009	3.701	0.010	3.525	0.009	3.482	0.009	3.519	0.009	3.438	0.009	3.464	0.009
India	3258.841	0.874	3240.650	0.869	3252.511	0.872	3251.964	0.872	3250.333	0.872	3256.246	0.873	3255.276	0.873
Canada	8.600	0.002	9.141	0.002	8.836	0.002	8.838	0.002	8.892	0.002	8.712	0.002	8.751	0.002
United States	95.934	0.001	93.177	0.001	96.403	0.001	94.832	0.001	94.521	0.001	96.258	0.001	96.111	0.001
Mexico	4.630	0.001	3.751	0.001	4.417	0.001	4.199	0.001	4.113	0.001	4.520	0.001	4.470	0.001
Rest of Latin America	28.646	0.006	33.228	0.007	29.851	0.006	30.680	0.006	31.146	0.006	29.229	0.006	29.495	0.006
Argentina	-1.495	-0.001	-1.215	-0.001	-1.512	-0.001	-1.355	-0.001	-1.326	-0.001	-1.501	-0.001	-1.487	-0.001
Brazil	-0.849	0.000	-0.472	0.000	-0.751	0.000	-0.664	0.000	-0.626	0.000	-0.799	0.000	-0.773	0.000
European Union	307.302	0.005	-57.166	-0.001	169.191	0.003	132.836	0.002	95.083	0.001	238.249	0.004	212.788	0.003
Rest of Europe	34.453	0.005	12.609	0.002	23.994	0.004	22.683	0.003	20.641	0.003	28.763	0.004	27.174	0.004
North Africa and Middle East	97.697	0.012	98.229	0.012	98.599	0.012	97.591	0.012	97.676	0.012	98.047	0.012	98.143	0.012
Rest of Sub-Saharan Africa	72.242	0.045	71.811	0.044	72.541	0.045	71.872	0.045	71.844	0.044	72.348	0.045	72.351	0.045
South Africa	12.611	0.014	12.464	0.014	12.619	0.014	12.529	0.014	12.517	0.014	12.611	0.014	12.608	0.014
Tanzania and Uganda	1.482	0.011	1.468	0.011	1.496	0.011	1.465	0.011	1.465	0.011	1.487	0.011	1.487	0.011
World	**9218.428**	**0.038**	**7704.465**	**0.031**	**8740.582**	**0.036**	**8432.964**	**0.034**	**8291.338**	**0.034**	**8961.429**	**0.036**	**8868.709**	**0.036**

Source: Authors' results from simulations

rice. Therefore, in most cases, sensitive countries gain overall from the adoption of GM rice.

Discussion

The results of our international economy-wide simulations vary across regions and scenarios, but they share a number of similarities, that can help us draw a few general lessons. First, our simulations show that the adoption of GM rice by India and/or China would result in significant economic gains in these countries and globally in the presence or absence of trade restrictions in certain sensitive countries. Only a few regions experience net losses with the adoption of GM rice, and these losses are relatively insignificant, except perhaps in sensitive countries with trade bans or when segregation results in a 5% additional trade cost for their non-GM rice imports. However, these developed countries have adopted restrictive policies in the presence of positive consumer willingness to pay to avoid GM food products, so these relatively small real income losses might not be actual welfare losses. At the same time, under our assumptions, the model shows that adopting GM rice in China and India results in significant economic gains, based on technical efficiency gains, and associated with large increases in rice production and large reduction of imports.

Table 8: Relative Effects of Trade Restriction on Total Gains from GM Rice Adoption for Selected Countries in the Three Sets of Scenarios

Set	**C**		**I**		**CI**	
Scenarios	1 vs. 2a	1 vs. 2b	1 vs. 2a	1 vs. 2b	1 vs. 2a	1 vs. 2b
China	0.51%	0.17%			0.51%	0.17%
India			0.59%	0.21%	0.56%	0.19%
World	23%	7.0%	5.9%	2.3%	16.4%	5.2%

Source: Simulation results

Secondly, our simulations show that trade regulations would affect the gains from GM rice adoption, but that this effect is insignificant compared to the gains with the adoption of GM rice. A complete import ban of rice from GM producing countries in sensitive countries results in lower gains for an exporter like India. Similarly, applying a trade filter that allows only products for intermediate consumption to enter sensitive countries, reflecting the effects of current labeling regulations on GM food, slightly reduces the gains of exporting GM adopting countries. Yet, even with these barriers, China or India would largely gain from the adoption of GM rice, because their relative loss with trade restrictions is very small compared to the productivity gains they experience domestically. To emphasize this result, Table 8 shows the relative change in gains from GM rice under the most restrictive scenarios of each set. Even if globally, the gains are reduced by up to 23% overall (in the first set), we find that the reduction in gains for India or China is less or equal to 0.6% of the overall gains they obtain with GM rice. This means that for each 100 dollars of real income gains with GM rice, China or India would risk losing 60 cents due to the possible ban in import-sensitive countries.

Table 9: Opportunity Cost of Segregation of non-GM Rice for Adopting and Sensitive Countries ($ million/year)

$million/year	Country	Segregation of non-GM rice for final consumption only			Segregation of non-GM rice for final and intermediate consumption		
SET		**C**	**I**	**CI**	**C**	**I**	**CI**
	China	3.1	0.1	2.9	9.8	0.2	10.3
	India	-0.1	3.7	3.7	-0.3	10.9	11.3
Total GM producers		**3.1**	**3.7**	**6.6**	**9.8**	**10.9**	**21.6**
	Australia-NZ	-0.1	0.3	0.2	-1	0.3	-0.8
	Japan	126.1	5.0	131.2	330	14	345
	South Korea	11.3	0.4	11.6	162.2	4.3	168.3
	EU	32.6	34.2	69.1	90.3	86.5	190
	Rest of Europe	3.6	1.1	4.8	7.4	2.5	10
Total sensitive countries		**173.5**	**41**	**216.9**	**588.9**	**107.6**	**712.5**
Global		**175.3**	**43.3**	**220.9**	**597.8**	**114.5**	**728.5**

Source: Authors' derivations

Thirdly, the use of segregation for non-GM crops can help offset some of these relatively minor losses for GM rice adopters, even at a 5% costs. Estimates of the opportunity costs of segregation are reported for selected countries in Table 9. We can draw several conclusions from these derivations. First, these results show that GM producing countries have a positive but relatively limited opportunity cost of segregation, ranging from $3 to 4million/year for final rice product to about $7 million per year for rice going towards intermediate consumption. Second, segregation would be as valuable for China as for India, even if segregation would be globally much more valuable when China adopts than when India adopts GM rice. Third, we find that segregation of non-GM rice for intermediate consumption would matter more than segregation of non-GM rice for final consumption.

More generally, we find that most of the global benefits of segregation would occur in importing sensitive countries themselves. For instance, when the two countries adopt GM rice, segregating non-GM rice for final consumption results in global gains of $221 million per year, of which $217 million would occur in sensitive countries and only $6.6 million in China and India. Similarly, under the same set, the segregation of non-GM rice for final and intermediate consumption results in increased gains of about $728m per year, of which $712 million would go to sensitive countries and only $21 million to GM rice adopters. Consequently, these results suggest that the adoption of GM rice in India or China may not necessarily require high investment by traders willing to keep their market in sensitive countries. Because the immediate cost of bans will largely be borne by importers, they will have a clear incentive to invest in segregation or at least to make sure GM rice is approved and the import bans are replaced by trade filters.

Fourth, we find that India and China can act independently on GM rice, because they do not share competing interests. The gains to China remain the same if India adopts GM rice or if it does not, despite the relative price decline with both countries adopting. Similarly, the gains to India remain the same, whether China adopts or not. But the order of leadership makes a small difference. If China leads the world by adopting GM rice, India would incur very small losses in rice export, and suffer a small and relatively insignificant decline in real income if it does not follow China. On the other hand, if India adopts GM rice first, China would actually gain a small and relatively insignificant welfare amount, even if it slightly reduces its exports of rice. We would expect the same type of effect with other net exporting or small exporting and importing countries: large exporters will loss from a rival adopting a productivity enhancing technology, while small exporters and importers will not necessarily lose and may even gain from it.

Overall, we obtain larger gains for GM rice in India or globally than previous studies. For China, our results can be compared to the ones of Huang et al. (2004). Our slightly larger results likely come from the fact that unlike Huang et al. (2004), we do not explicitly reduce the gains from GM crops due to the price of seeds. Therefore the gains presented here include the returns to the developers and adopting producers together. For India, our results are much larger than the ones in other studies. The difference may come from the selected productivity shock, the adoption rate, or the scenarios. Because we impose factor-biased productivity shocks with large efficiency gains in certain critical sectors, our results may be different from the imposition of a Hicks-neutral 5% shock with GM rice. Moreover, as we combine the effects of different traits, the total effect of GM rice in our model is quite large compared to only Bt rice or drought resistant rice. Hareau et al. (2005) also differentiate traits but they do not impose a shock on the chemical or labor factor for Bt rice.

Despite the differences with previous studies, we believe that our results are likely to be robust for India, in particular because they rely on primary and secondary data on productivity potential rather than generalized parameters. Still, like any ex-ante simulation exercise, the results depend on the assumptions of the model and scenarios. One of the critical factors is the yield effect. To verify the validity of the results we ran four sets of additional simulations (for scenarios 1, 2a, 3a-i and 3a-ii) using the minimum and maximum values for yields in India presented in Table 2. The results are shown in Table A6 in the Appendix. As expected, the welfare effects are consistently lower for India with the minimum yield effects than with the most likely yield effects. The welfare effects are also consistently larger for India with maximum yield gains, which means that the price decline with this higher rice production is still compensated by larger gains for India overall. At the same time, the relative differences across scenarios are proportionally similar to the ones with most likely gains. India gains most under scenario 1 and least under scenario 2a, and segregation of non-GM rice compensates for the small reduction in gains with rice trade bans.

Table 10: Welfare Gains per percent Actual Adoption of GM Rice in each Scenario ($ million)

SET	Country	1	2a	2b	3a-i	3a-ii	3b-i	3b-ii
C	China	57.9	57.6	57.8	57.7	57.7	57.8	57.8
I	India	45.5	45.2	45.4	45.4	45.3	45.4	45.4
CI	China	57.9	57.6	57.8	57.8	57.7	57.9	57.8
	India	45.4	45.2	45.3	45.3	45.3	45.4	45.4

Source: Authors' derivations

A second critical factor is the adoption rate. To provide a consistent idea of the welfare gains experienced by the countries in our study, we divided the total annual real income gains by the final adoption rates (presented in Table 3). The results are shown in million dollars per year per percentage of adoption in Table 10. We find that the gains are fairly homogeneous across scenarios. China gains just under $58 million for each percentage point of Bt rice in total rice production, while India gains above $45 million for each percentage point of the GM rice with our combination of traits. The difference between the two countries is mainly due to the total value of rice production and in the assumptions we made in the two countries. In any case, these result show that GM rice would be largely beneficial even at a lower adoption rate.

Conclusions

Many developing countries have delayed the adoption of GM crops for fear of losing export markets in the EU and other countries with stringent regulations on the approval and marketing of GM food. Yet, previous trade studies have shown that despite the presence of these importing countries´ regulations, the production of relevant GM crops in developing countries is still expected to provide significant net welfare gains (Anderson and Jackson, 2005).

In this paper we study the potential effects of introducing GM rice in India with or without China. We focus on four types of GM rice resistant to biotic and abiotic stresses, such as drought resistant rice and use a multi-country, CGE model to simulate their introduction in India. We build on previous international simulation models by improving the representation of the productivity shocks with GM rice taking into account regional and land type disparities and by using an updated representation of the world market, accounting for the short run and long run effects of import approval and labeling policies in sensitive countries. We also allow for the possibility of segregation for non-GM rice products going towards sensitive importing countries.

First, the results of our simulations show that the gains associated with the partial adoption of our combination of traits for GM rice in India are quite significant, accounting for about 0.9% of total real income or over $3.2 billion annually. Our results show that a 1% increase in the adoption of GM rice in India, combining different traits in different regions, would result in total welfare gains exceeding $45 million per year, with or without trade blocks in sensitive countries. Similarly, using the assumptions made by Huang et al. (2004), we find that a 1% increase in Bt rice in China would result in gains exceeding $57 million per year.

Second, we find that these results largely exceed any type of potential trade losses for India. In India like in China, with GM rice, even at partial adoption rates, the losses with trade restrictions does not exceed 0.6% of the total gains with GM rice adoption. Provided it is adopted, GM rice would also result in large production increases, which could result in relative welfare gains in countries of Sub-Saharan Africa or rice importing countries of Asia. At the same time, we find that segregation can help reduce a significant share of the potential welfare gain reductions due to trade losses for GM rice adopters that want to keep export opportunities in sensitive countries. Our results also show that the opportunity cost of segregation for non-GM rice is much larger for sensitive importing countries than exporting countries adopting GM rice. This suggests that importers will likely have the incentive to invest into segregation chains for non-GM supplies to mitigate their expected losses due to the introduction of GM crops in exporting countries.

Therefore, our results demonstrate that some of the perceived trade losses related to the use of GM rice, a major food crop in Asia are exaggerated in the current market situation. It is certain that trade barriers could multiply with the adoption of trade distorting regulations in a larger set of countries. For instance, India is exporting more rice towards North African and the Middle East than towards Europe, and some of these countries could decide to enforce strict import policies. But a large share of the economic losses with these possible restrictions would likely incur in these particular countries. Still, in the current regulatory environment, where enforced regulations are concentrated in a few importers, India and China are bound to largely gain from adopting GM rice. Because India and China have very large population bases with high consumption rates, any increase in rice productivity will most likely overcome any potential trade losses.

Third, we find that there is no significant first mover-advantage for GM rice in India and China even if India would be slightly better off leading than following on the adoption of GM rice. China and India would gain as much by adopting GM rice if the other adopts it than if it does not. At the same time, India might incur small losses if China adopts GM rice at a significant level, because of its potential loss in competitiveness, while China would not lose and would potentially gain a little if it waited for India to be first. If we consider our assumptions to be relatively conservative (e.g., with weighted average of yield effects from different data sources), it is possible that India would be better off leading in technology adoption, but our results are not sufficient to warrant that conclusion. Still, our main conclusion is that China and India would largely gain from GM rice adoption, even when faced with trade restrictions in sensitive countries. China faces even less potential economic risk than India, and should be encouraged to move ahead, given its technology edge in GM rice. Such a move would clearly encourage India to follow, provided GM rice can be approved by its biosafety authorities.

Even if our simulations are based on improvements in assumptions and scenarios, they are still subject to a number of limitations. First, like in any ex-ante simulation, the productivity effects are still largely uncertain and their level affects the results significantly. A sensitivity analysis on the yield factors showed that larger yield gains result in higher welfare gains, but that the losses with trade remain relatively small compared to the gains with GM technology. More sensitivity analysis, particularly on the input factors would help to provide a more complete picture of the range of possible effects of GM rice in India. Second, our simulation would gain by using a dynamic rather than comparative static framework. Local expert meetings and elicitation provided some insight into the potential evolution of adoption in India. Accounting for the crop/trait specific regulatory lag, extension lags and adoption dynamics would help improve the plausibility of our results and allow us to introduce more strategic considerations. If not, the use of a more recent representation of the economy would at least provide a better overview of the situation. Third, despite our effort to reduce potential biases linked to the over-aggregation of the GTAP database with the use of proportional factors for agricultural chemical, our model would be better served with structural differentiation within the chemical sector.

More generally, it is necessary to keep in mind that the results of our global simulations, like the ones of other papers, do not account for the positive or negative effects of technology adoption on the environment and other potential externalities they may generate on other activities of the economy. On the one hand, the reduction of chemical inputs may provide benefit for farmers' health and/or the environment, on the other hand, secondary or non-target pest resistance building may affect other types of crop production and potential gene flows could affect natural biodiversity. Our implicit assumption throughout the chapter is that the varieties of GM rice we consider are only released after assessment and approval by the biosafety regulatory authorities in India and China, on the conclusion that their potential risks are negligible or at least manageable under particular practices. Naturally any possible external costs incurred in adopting countries would have to be compared with the large expected income gains we found in these two countries.

References

Anderson, K. and L.A. Jackson. "Some Implications of GM Food Technology Policies for Sub-Saharan Africa," *Journal of African Economies* 14 (2005): 385-410.

Anderson, K., L.A. Jackson, and C.P. Nielsen. "Genetically Modified Rice Adoption: Implications for Welfare and Poverty Alleviation," World Bank Policy Research Working Paper No. 3380. Washington, DC: World Bank (2004)

Anderson, K. and S. Yao. "China, GMOs and World Trade in Agricultural and Textile Products," *Pacific Economic Review* 8 (2003): 157-69.

Annou, M.M, F.H. Fuller, and E.J. Wailes. "Innovation Dissemination and the Market Impacts of Drought-Tolerant, Genetically Modified Rice," *International Journal of Biotechnology* 7(2005):113-127.

Bchir, M.H., Y.Decreux, J-L. Guerin, and S. Jean. "MIRAGE, a Computable General Equilibrium for Trade Policy Analysis," Working Paper No. 2002-17. Paris: Centre d'Etudes Prospectives et d'Informations Internationales (2002).

Bennett, R.M., Y. Ismael, U. Kambhampati, and S. Morse. "Economic Impact of Genetically Modified Cotton in India," *AgBioForum* 7 (2004): 96-100.

Berwald, D., C.A. Carter, and G.P. Gruere. "Rejecting New Technology: The Case of Genetically Modified Wheat," *American Journal of Agricultural Economics* 88 (2006):432-447.

Elbehri, A. and S. MacDonald. "Estimating the Impact of Transgenic Bt Cotton on West and Central Africa: A General Equilibrium Approach," *World Development* 32 (2004): 2049-64.

Evenson, R.E., R.W. Herdt, and M. Hossain. *Rice Research in Asia: Progress and Priorities*. Wallington: CAB International (1996).

Fischer, G., H. van Velthuizen, M. Shah, and F. Nachtergaele. "Global Agro-ecological Assessment for Agriculture in the 21st Century: Methodology and Results," No. RR-02-02. Laxenburg: Institute for Applied Systems Analysis (2002).

Gruere, G.P. "An Analysis of Trade Related International Regulations of Genetically Modified Food and their Effects on Developing Countries," EPTD Discussion Paper No. 147. Washington, DC: International Food Policy Research Institute (2006).

Gruere, G.P. and S.R. Rao. "A Review of International Labeling Policies to Evaluate India's Proposed Rules," *AgBioForum* 10 (2007): 51-64.

Hareau, G., G.W. Norton, B.F. Mills, and E. Peterson. "Potential Benefits of Transgenic Rice in Asia: A General Equilibrium Analysis," *Quarterly Journal of International Agriculture* 44 (2005): 205-21.

Huang, J., R. Hu, H. van Meijl, and F. van Tongeren. "Biotechnology Boosts to Crop Productivity in China: Trade and Welfare Implications," *Journal of Development Economics* 75 (2005): 27-54.

Hertel, T. W. (ed). *Global Trade Analysis: Modeling and Applications*. New York: Cambridge University Press (1997).

International Food Policy Research Institute. "An Economic Analysis of Domestic and International Biosafety and Marketing Regulations for Agricultural Biotechnology in India and Bangladesh," Unpublished Donor Report. Washington, DC: International Food Policy Research Institute (April September 2005).

James, C. ISAAA. "Global Status of Commercialized Biotech/GM Crops: 2006," ISAAA Brief No. 35-2006 (2006).

Paarlberg, R.L. "The Real Threat to GM Crops in Poor Countries: Consumer and Policy Resistance in Rich Countries," *Food Policy* 27 (2002): 247-50.

Pray, C., J. Huang, R. Hu, and S. Rozelle. "Five Years of Bt Cotton in China - The Benefits Continue," *The Plant Journal* 31 (2002): 423-30.

Runge, C.F. and B. Ryan. "The Global Diffusion of Plant Biotechnology: International Adoption and Research in 2004," Minneapolis-St.Paul, MN: University of Minnesota, Center for International Food and Agricultural Policy (2004).

Sánchez, P.A, W. Couto, and S.W. Buol. "The Fertility Capability Soil Classification System: Interpretation, Applicability and Modification," *Geoderma* 27 (1982): 283–309.

Smale, M., P. Zambrano, J. Falck-Zepeda, and G. Gruere. "Parables: Applied Economics Literature about the Impacts of Genetically Engineered Varieties in Developing Economies," EPTD Discussion Paper No. 158. Washington, DC: International Food Policy Research Institute (October 2006).

Smith, C., R. Yost, J. Benites, and F. Nachtergaele. "Fertility Capability Classification (FCC) System - 3rd Approximation: The Algorithm and an Application." Paper No. 862 in *16th World Congress of Soil Science*, A. Ruellan (ed.). Montpellier: International Society of Soil Science (1988).

You, L. and S. Wood. "An Entropy Approach to Spatial Disaggregation of Agricultural Production," *Agricultural Systems* 90 (2006): 329-347.

Yudelman, M., A. Ratta, and D. Nygaard. "Pest Management and Food Production: Looking to the Future," 2020 Food Agriculture and the Environment Discussion Paper No. 25. Washington, DC: International Food Policy Research Institute (1998).

Appendix: Additional Tables

Table A1: Decomposition of the Welfare Gains for Scenario 1 under each Set (% of total real income)

SET	Country	Real income	Allocation efficiency gains	Terms of trade gains	Other gains
C	China	0.60	0.04	0.03	0.53
	India	0.00	0.00	0.00	0.00
I	China	0.00	0.00	0.00	0.00
	India	0.88	0.14	-0.01	0.74
CI	China	0.60	0.04	0.03	0.53
	India	0.87	0.14	-0.01	0.75

Source: Results from simulations

Table A2: % Change in Average World Price of Rice Under Different Scenarios

Scenario	China	India	India + China
1	-0.634	-0.826	-1.502
2a	-0.383	-0.665	-1.067
2b	-0.587	-0.797	-1.423
3a-i	-0.568	-0.811	-1.419
3a-ii	-0.520	-0.764	-1.348
3b-i	-0.634	-0.831	-1.504
3b-ii	-0.597	-0.792	-1.453

Source: Results from simulations.

Table A3: % Changes in Production, Export and Import Volumes of Rice for Set C Scenarios in Selected Countries

Country	% change in	1	2a	2b	3a-i	3a-ii	3b-i	3b-ii
China	Production	20.1	18.2	19.9	18.9	18.8	19.9	19.9
	Exports	27.3	-11.7	13.7	56.7	41.0	36.9	23.6
	Imports	-46.9	-47.6	-47.1	-47.3	-47.3	-47.0	-47.1
India	Production	-0.4	0.0	-0.4	-0.2	-0.6	-0.4	-0.8
	Exports	-5.7	-1.9	-4.7	-3.6	-7.7	-5.1	-9.0
	Imports	-1.3	-1.9	-1.3	-1.6	-1.9	-1.3	-1.5
Japan	Production	-2.1	1.8	-1.5	0.0	0.4	-1.7	-1.5
	Exports	-2.8	-4.2	-3.0	-3.6	-3.7	-2.9	-2.9
	Imports	-4.2	0.7	-2.9	11.7	8.8	1.4	-1.5
EU	Production	-6.8	5.4	-5.9	0.0	2.6	-6.3	-4.5
	Exports	-5.0	-5.5	-3.7	-5.5	-5.9	-4.3	-4.6
	Imports	-7.1	3.8	-4.8	8.2	3.8	-2.7	-7.4
Rest of Asia	Production	-1.7	-1.1	-1.6	-1.4	-1.3	-1.6	-1.6
	Exports	-8.5	-6.4	-7.8	-7.4	-7.0	-8.1	-7.8
	Imports	-1.9	-3.2	-2.1	-2.7	-2.7	-2.0	-2.0

Source: Results from simulations

Table A4: % Changes in Production, Export and Import Volumes of Rice for Set I Scenarios in Selected Countries

Country	% change in	1	2a	2b	3a-i	3a-ii	3b-i	3b-ii
China	Production	-0.1	0.0	-0.1	-0.1	-0.3	-0.1	-0.3
	Exports	-5.8	-4.9	-4.9	-4.3	-11.3	-5.4	-12.3
	Imports	1.0	0.9	1.0	0.9	0.8	1.0	0.8
India	Production	21.0	17.0	20.8	19.0	18.6	20.9	20.7
	Exports	26.1	17.7	17.7	39.3	31.3	30.5	23.1
	Imports	-50.7	-50.9	-50.9	-50.9	-51.0	-50.8	-50.8
Japan	Production	-0.3	-0.1	-0.2	-0.2	0.2	-0.2	0.2
	Exports	-2.5	-2.4	-2.4	-2.3	-2.5	-2.4	-2.6
	Imports	0.4	0.9	0.3	0.9	-2.1	0.6	-2.4
EU	Production	-7.1	6.5	-6.1	-1.2	1.6	-6.6	-4.6
	Exports	-5.8	-5.6	-5.6	-7.3	-7.7	-5.7	-6.0
	Imports	-4.7	11.8	-5.0	11.8	7.0	0.1	-5.1
Rest of Asia	Production	-1.2	-0.9	-1.2	-1.1	-1.0	-1.2	-1.1
	Exports	-7.3	-6.8	-6.8	-6.5	-6.1	-7.0	-6.7
	Imports	-1.6	-1.5	-1.5	-1.5	-1.6	-1.6	-1.7

Source: Results from simulations

Table A5: % Changes in Production, Export and Import Volumes of Rice for Set CI Scenarios in Selected Countries

Country	% change in	1	2a	2b	3a-i	3a-ii	3b-i	3b-ii
China	Production	19.8	18.0	19.6	18.8	18.6	19.7	19.6
	Exports	20.6	7.6	7.6	51.4	35.8	30.5	17.6
	Imports	-46.4	-46.6	-46.6	-46.8	-46.9	-46.5	-46.6
India	Production	20.2	16.6	20.0	18.7	18.2	20.1	19.9
	Exports	19.7	12.1	12.1	35.4	27.3	24.7	17.6
	Imports	-51.3	-51.5	-51.5	-51.7	-51.8	-51.4	-51.4
Japan	Production	-2.3	1.7	-1.7	-0.1	0.2	-2.0	-1.7
	Exports	-5.1	-5.1	-5.1	-5.7	-5.8	-5.1	-5.2
	Imports	-3.7	-2.5	-2.5	12.7	9.8	2.1	-0.8
EU	Production	-12.7	13.3	-10.9	-1.2	1.5	-11.9	-10.5
	Exports	-10.4	-8.8	-8.8	-12.0	-12.3	-9.6	-9.8
	Imports	-9.8	-8.9	-8.9	21.9	16.8	-0.7	-6.1
Rest of Asia	Production	-2.8	-1.8	-2.7	-2.4	-2.3	-2.7	-2.7
	Exports	-15.1	-14.0	-14.0	-13.4	-13.0	-14.6	-14.3
	Imports	-3.3	-3.4	-3.4	-4.0	-4.1	-3.4	-3.4

Source: Results from simulations

Table A6: Change in Welfare Effects with GM Rice Adoption in India and China, under Minimum, Most Likely and Maximum Yield Effects for India in the Case of Selected Scenarios ($ million/year)

Set CI	1. Productivity shock			2a. Import ban, no segregation			3a-i. Import ban, costless segregation			3a-ii. Import ban, 5% segregation cost		
Region	Minimum	Most likely	Maximum	Minimum	Most likely	Maximum	Minimum	Most likely	Maximum	Minimum	Most likely	Maximum
Australia and NZ	-4.624	-4.959	-5.280	-3.082	-3.528	-3.963	-3.903	-4.276	-4.616	-3.763	-4.151	-4.512
China	4633.076	4633.467	4633.918	4609.292	4609.906	4610.572	4619.637	4620.240	4620.903	4617.649	4618.276	4618.966
Japan	462.008	472.340	483.624	-294.727	-288.651	-282.297	46.955	56.301	67.048	-20.450	-11.778	-1.929
South Korea	175.953	178.413	181.170	-157.071	-155.699	-154.217	10.187	12.564	15.419	-20.836	-18.638	-16.022
Rest of Asia	5.346	1.535	-1.509	10.523	7.360	4.956	7.138	3.275	0.023	7.730	3.962	0.816
Indonesia	6.677	8.500	10.354	7.343	9.222	11.138	6.997	8.828	10.679	7.063	8.902	10.763
Philippines	5.079	5.656	6.255	3.936	4.481	5.045	4.503	5.081	5.685	4.395	4.968	5.567
Bangladesh	2.407	3.382	4.436	2.656	3.701	4.826	2.500	3.482	4.527	2.527	3.519	4.576
India	2287.077	3258.841	4200.295	2272.197	3240.650	4178.408	2280.720	3251.964	4193.407	2279.559	3250.333	4191.185
Canada	7.820	8.600	9.453	8.328	9.141	10.027	8.058	8.838	9.683	8.107	8.892	9.742
United States	87.591	95.934	104.467	85.323	93.177	101.220	86.563	94.832	103.374	86.324	94.521	102.980
Mexico	4.193	4.630	5.119	3.343	3.751	4.209	3.764	4.199	4.690	3.683	4.113	4.600
Rest of L. America	28.715	28.646	28.593	33.126	33.228	33.346	30.782	30.680	30.548	31.224	31.146	31.042
Argentina	-1.020	-1.495	-1.986	-0.745	-1.215	-1.701	-0.880	-1.355	-1.847	-0.851	-1.326	-1.817
Brazil	-0.629	-0.849	-1.076	-0.282	-0.472	-0.668	-0.449	-0.664	-0.892	-0.415	-0.626	-0.848
European Union	273.696	307.302	343.115	-69.058	-57.166	-44.103	100.990	132.836	171.042	66.467	95.083	129.370
Rest of Europe	32.081	34.453	37.138	11.009	12.609	14.473	20.478	22.683	25.334	18.552	20.641	23.144
N. Africa and M. East	76.043	97.697	119.926	76.151	98.229	120.912	75.875	97.591	119.797	75.901	97.676	119.954
Rest of S-S Africa	63.554	72.242	81.054	62.989	71.811	80.781	63.157	71.872	80.690	63.112	71.844	80.686
South Africa	9.115	12.611	16.037	8.944	12.464	15.916	9.026	12.529	15.955	9.011	12.517	15.948
Tanzania and Uganda	1.166	1.482	1.805	1.143	1.468	1.801	1.147	1.465	1.788	1.146	1.465	1.789
World	**8155.321**	**9218.428**	**10256.905**	**6671.335**	**7704.465**	**8710.683**	**7373.246**	**8432.964**	**9473.238**	**7236.134**	**8291.338**	**9325.999**

Source: Results from simulations